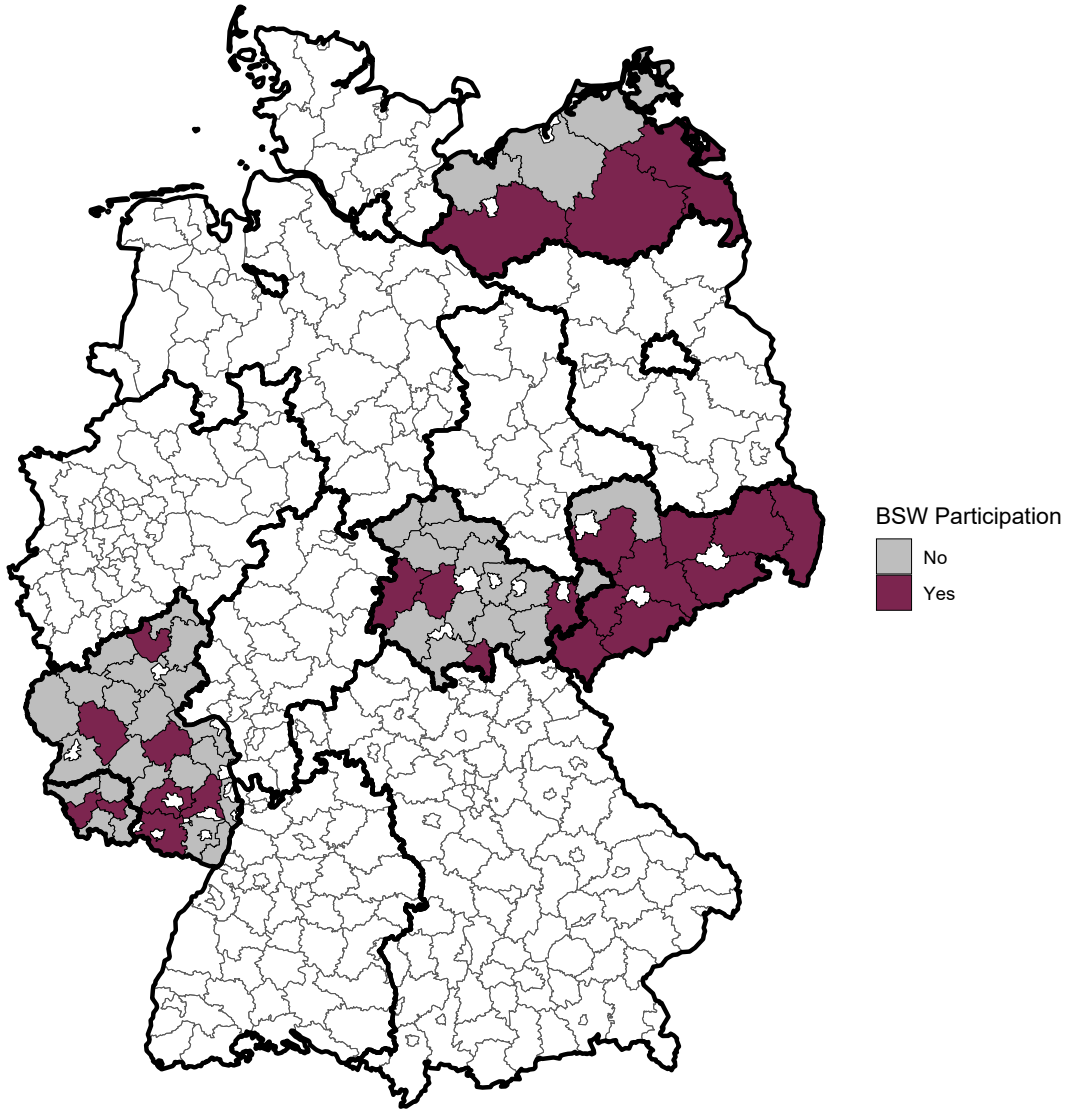
Supplementary Material: Challenging the Challengers? The Transformative Implications of the Bündnis Sahra Wagenknecht for German Party Competition

Stefan Eschenwecker & Thomas König

Figure A1: Map of States, Counties, and County-free Cities in Germany: Inclusion in Main Sample and Treatment Status



Note: Thick lines represent state borders, while thin lines indicated county and county-free city borders. White spots denote areas not included in the main sample. Shape files obtained from Bundesamt für Kartographie und Geodäsie (2024).

Formalized Identification Assumptions

We adopt the potential outcomes framework (Rubin 1974) to specify the assumptions necessary to credibly estimate the causal effect of BSW participation in the quasi-experiment of the 2024 County Council elections in Germany. For each municipality $(i = 1, 2, ..., n)$, let the treatment assignment, i.e., whether BSW ran in the County Council election, be denoted by $T_i \in \{0, 1\}$, where 0 refers to the control group and 1 refers to the treatment group. Additionally, let X_i be a vector of pretreatment covariates and Y_i a scalar outcome. Then, $Y(1)$ and $Y(0)$ represent the potential outcomes, that is, the change in vote shares and turnout that Y_i would take on if BSW ran or did not run, respectively. As we aim to generalize our results beyond the specific local cases analyzed, our quantity of interest is the Average Treatment Effect (ATE). The ATE of BSW participation is defined as $\mathbb{E}[Y(1) - Y(0)]$. However, due to the fundamental problem of causal inference, we can only observe one outcome for each municipality. Thus, we require four additional assumptions to credibly estimate the causal effect in observational studies (Imbens 2004):

1. Stable Unit Treatment Value Assumption (SUTVA): SUTVA requires a constant treatment exposure and that potential outcomes for one unit are unaffected by the treatment assignment of other units: $Y_i(1), Y_i(0)$ are unaffected by $T_j \; \forall j \neq i$.

   The SUTVA assumption is tied to the conceptual identification strategy of the research design and carries two implications. First, it requires constant treatment exposure, which holds true in our case. The BSW either participates in a County Council election or it does not. While treatment intensity may be affected by distinct regional campaign efforts, this is unlikely to matter for County Council elections. County Councils have similar limited policy competencies, meaning that for the BSW it does not make sense to prioritize campaign efforts in some County Council elections over others. Second, SUTVA requires that the outcomes are not influenced by the treatment status of another municipality, meaning that no spillover effects between units should exist. This assumption is fulfilled, as the participation of the BSW in one county cannot influence voters' behavior in neighboring counties where the BSW is not listed on the ballot.

2. Conditional Independence: Outcome values need to be independent of the treatment assignment, conditional on pretreatment covariates: $(Y(1), Y(0)) \perp\!\!\!\perp T|X$.

   Conditional independence concerns confounding factors that influence both treatment assignment and outcomes. This is akin to assuming no omitted variable bias in conventional regression models conditional on the included control variables. With weighting methods, one should exclude outcome variables from the estimation process and include only pre-treatment covariates that are plausible

confounders, as the inclusion of irrelevant variables can exacerbate issues with common support and reduce the precision of estimates (Caliendo and Kopeinig 2008).

3. Covariate Balance: After applying CBPS weighting, the covariate distributions between municipalities in the control and treatment groups should be as similar as possible: $\mathbb{E}[X|T=1] = \mathbb{E}[X|T=0]$, which ensures a credible as-if randomization.

4. Common Support: This assumption requires that for every municipality, there is a positive probability of being assigned to both the treatment and control groups: $0 < P(T=1|X) < 1 \; \forall X$.

Table A1: Translation of Covariate Descriptions

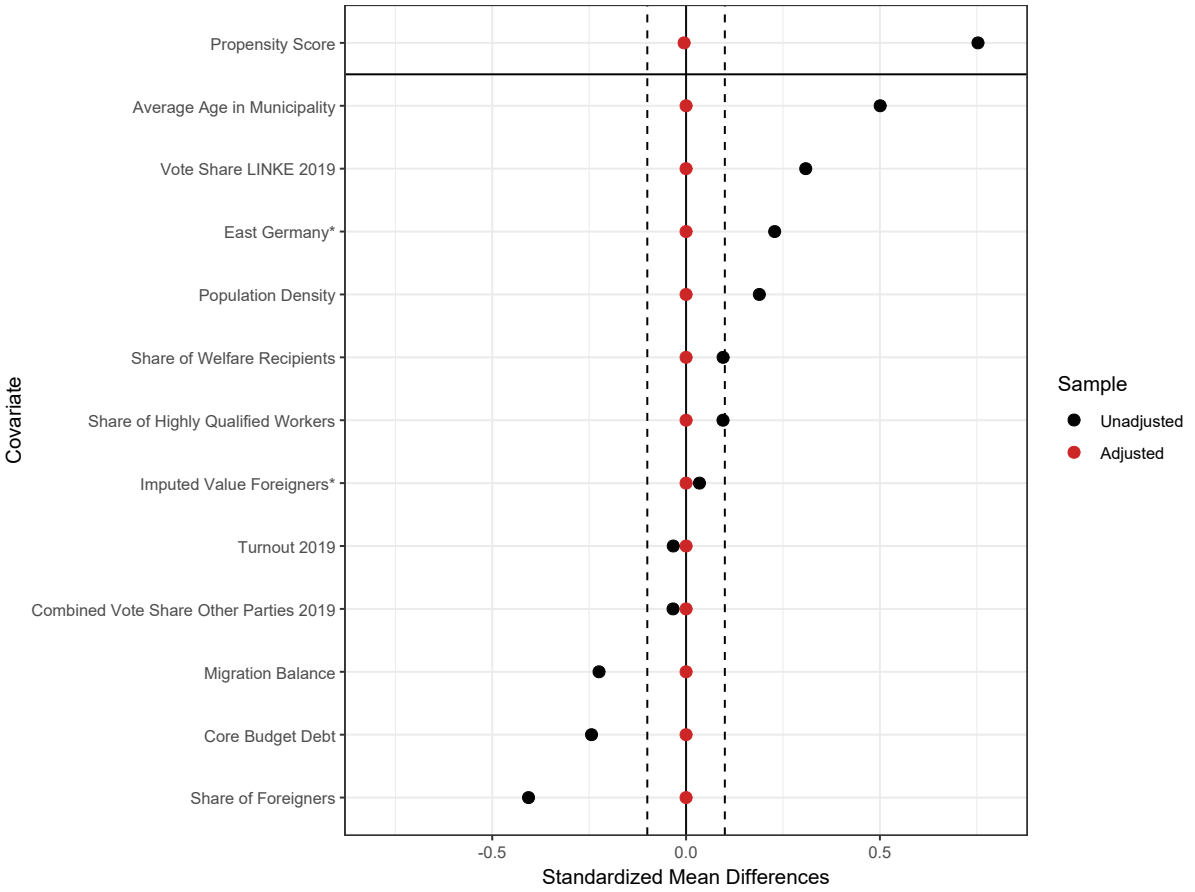
Covariate	Statement	Calculation
Share of Highly Qualified Workers	x % of the employed residents subject to social insurance in the municipality have an academic degree.	Employed residents with academic degree / Employed residents * 100
Migration Balance	In the year z, x persons per 1,000 persons of the resident population moved in more than moved out (or vice versa if the balance is negative).	(Immigrants - Emigrants) / Population * 1,000 (Each averaged over the last 4 years)
Average Age in Municipality	The average age of all persons in the municipality is x years.	Artihmetic mean
Population Density	There are x inhabitants per hectare of area.	Population / Area in Hectares
Share of Foreigners	x percent of the population are without German citizenship. (Data is only available at the county level for some federal states)	Number of foreign residents / Total number of residents * 100
Share of Welfare Recipients	x percent of the population under 65 years receive benefits according to SGB II	Number SGB II beneficiaries / Population under 65 years * 100
Core Budget Debt	In year z, the municipality y had debts in the core budget from loans amounting to x euros per inhabitant.	(Funded Debts + Cash Advances + Credit-like Transactions) / Inhabitants

Source: Bertelsmann Stiftung (2024).

Table A2: Summary Statistics on Full Sample Including Counties and County-free Cities

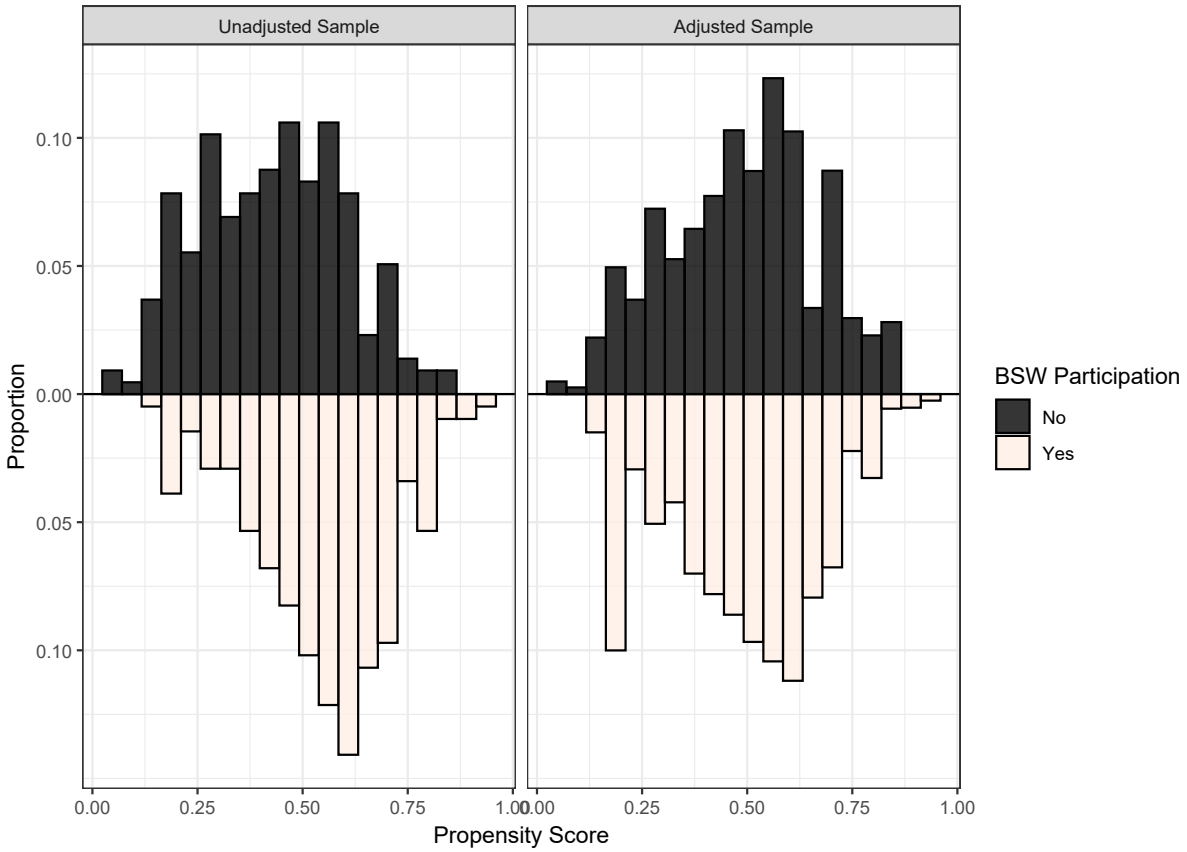
Variable	N	Mean	SD	Min	Max
Change Turnout	586	3.3	3.6	-18.1	15.1
Change Vote Share AfD	586	7.6	4.3	-5.7	21.5
Change Vote Share Greens	586	-4.0	1.9	-14.0	1.3
Change Vote Share FDP	586	-2.0	2.1	-16.6	17.6
Change Vote Share SPD	586	-2.1	3.4	-22.9	14.5
Change Vote Share CDU	586	-0.9	5.1	-34.0	14.9
Change Vote Share LINKE	586	-4.6	3.8	-27.1	1.7
BSW Participation	586				
... No	337	58%			
... Yes	249	42%			
East Germany	586				
... No	249	42%			
... Yes	337	58%			
Turnout 2019	586	61.7	6.6	42.5	78.7
Vote Share AfD 2019	586	14.8	7.4	0.0	37.7
Vote Share Greens 2019	586	9.5	5.2	1.7	27.8
Vote Share FDP 2019	586	5.4	3.3	1.0	30.4
Vote Share SPD 2019	586	17.1	9.5	0.0	41.0
Vote Share CDU 2019	586	30.7	8.2	11.0	58.9
Vote Share LINKE 2019	586	9.0	6.6	0.0	38.1
Population Density	586	2.9	3.0	0.3	22.6
Migration Balance	586	8.0	5.1	-17.6	33.3
Average Age in Municipality	586	47.4	2.1	41.3	53.4
Share of Foreigners	586	7.9	5.0	0.5	44.1
Imputed Value for Share Foreigners	586				
... No	536	91%			
... Yes	50	9%			
Share of Highly Qualified Workers	586	12.2	4.5	5.7	42.2
Share of Welfare Recipients	586	6.8	3.6	1.0	20.1
Core Budget Debt	586	1043.3	1193.6	0	10422
Change Turnout European Election	249	3.7	3.6	-11.2	19.2
Change AfD European Election	249	8.6	3.7	-6.0	21.9
Change Greens European Election	249	-4.8	1.5	-9.3	-1.9
Change FDP European Election	249	-1.7	1.4	-5.1	1.9
Change SPD European Election	249	-3.4	2.0	-14.6	0.8
Change CDU European Election	249	-2.0	2.4	-15.2	4.4
Change LINKE European Election	249	-6.3	3.2	-14.0	7.1
Turnout 2024	112	62.6	4.6	52.9	73.4
Turnout 2024 European Election	112	58.4	6.4	38.5	70.4
Difference Turnout Council vs. Europe	112	4.3	5.8	-4.7	20.2

Figure A2: Love Plot of Covariate Balance Comparing Standardized Differences in Means Before and After CBPS Weighting



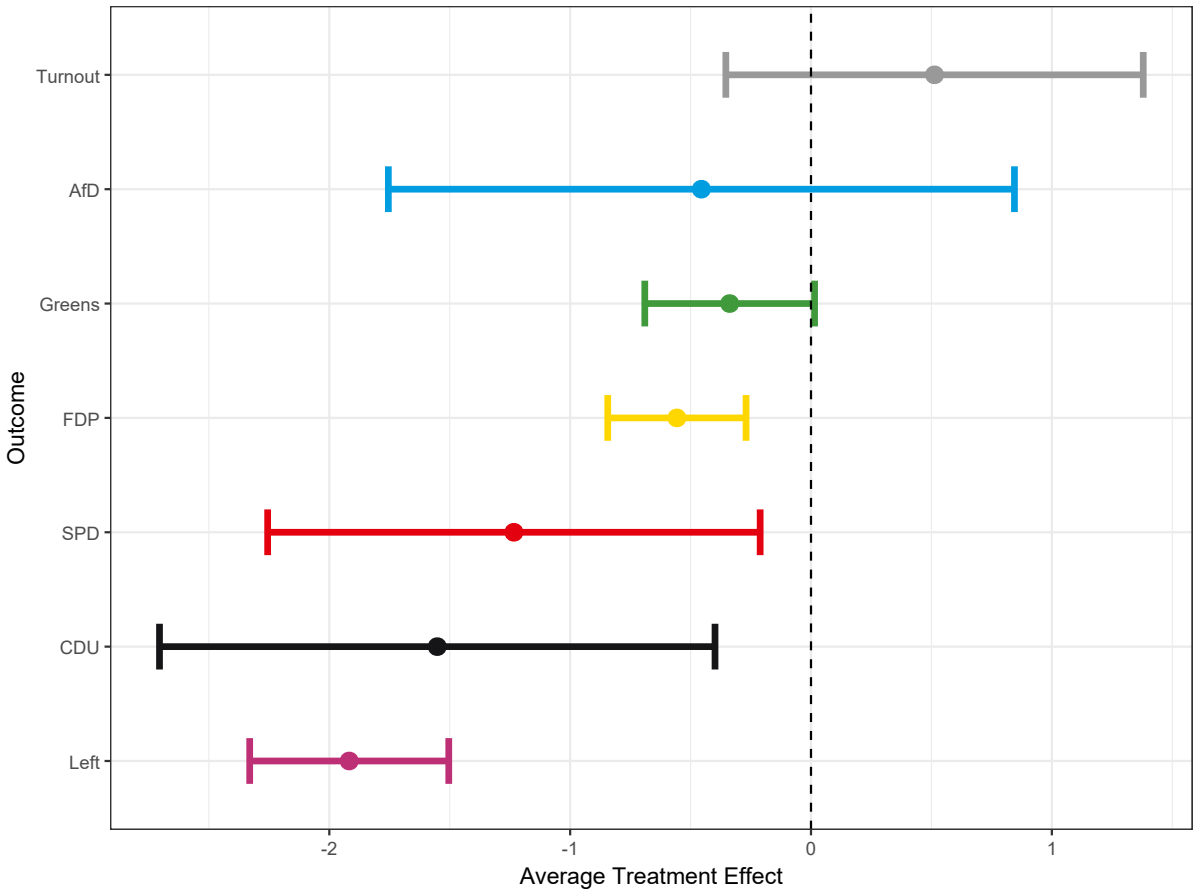
Note: Binary variables show raw differences in means. Weights were calculated using the *WeightIt* package for R (Greifer 2024b). Plot generated by the *cobalt* package for R (Greifer 2024a).

Figure A3: Distribution of Propensity Score Before and After CBPS Weighting by Treatment Status



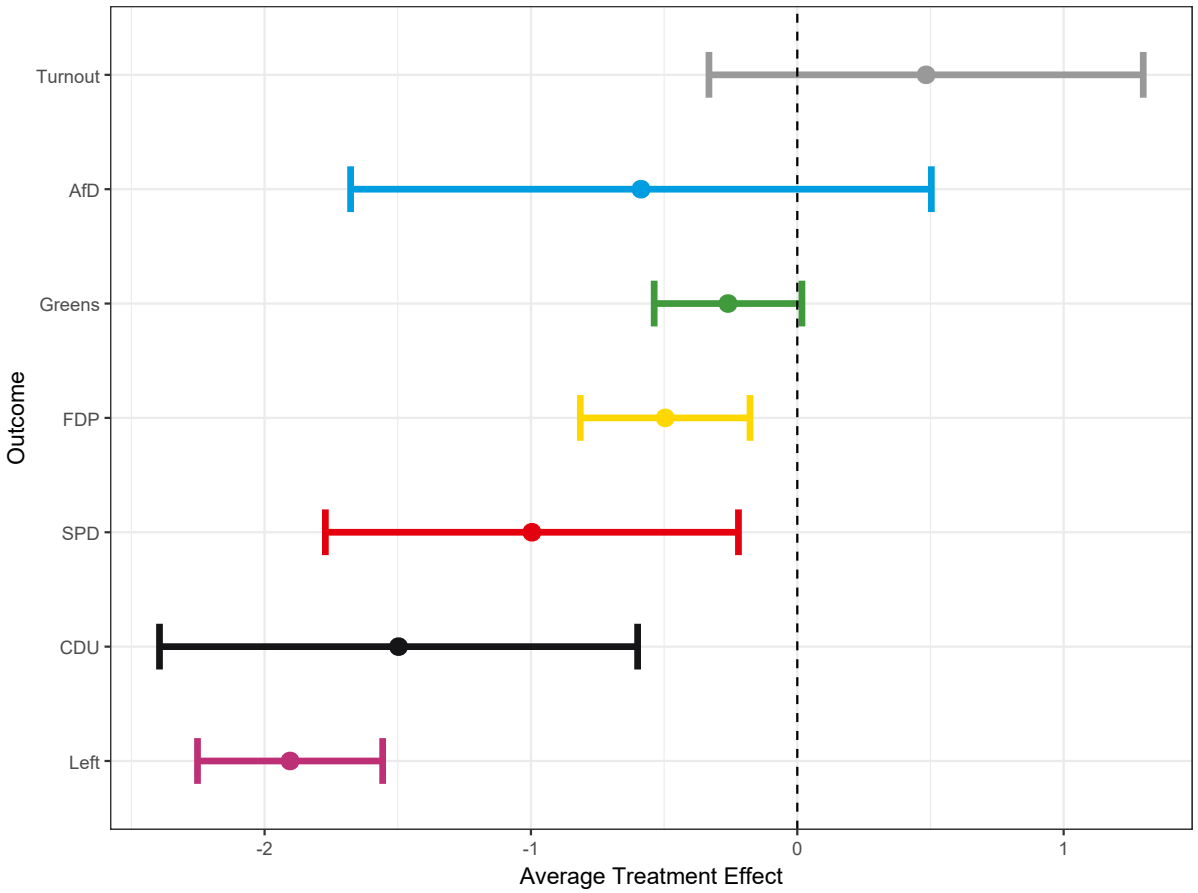
Note: Weights were calculated using the *WeightIt* package for R (Greifer 2024b). Plot generated by the *cobalt* package for R (Greifer 2024a).

Figure A4: Robustness Check: Hierarchical Model With Random Intercepts for Counties



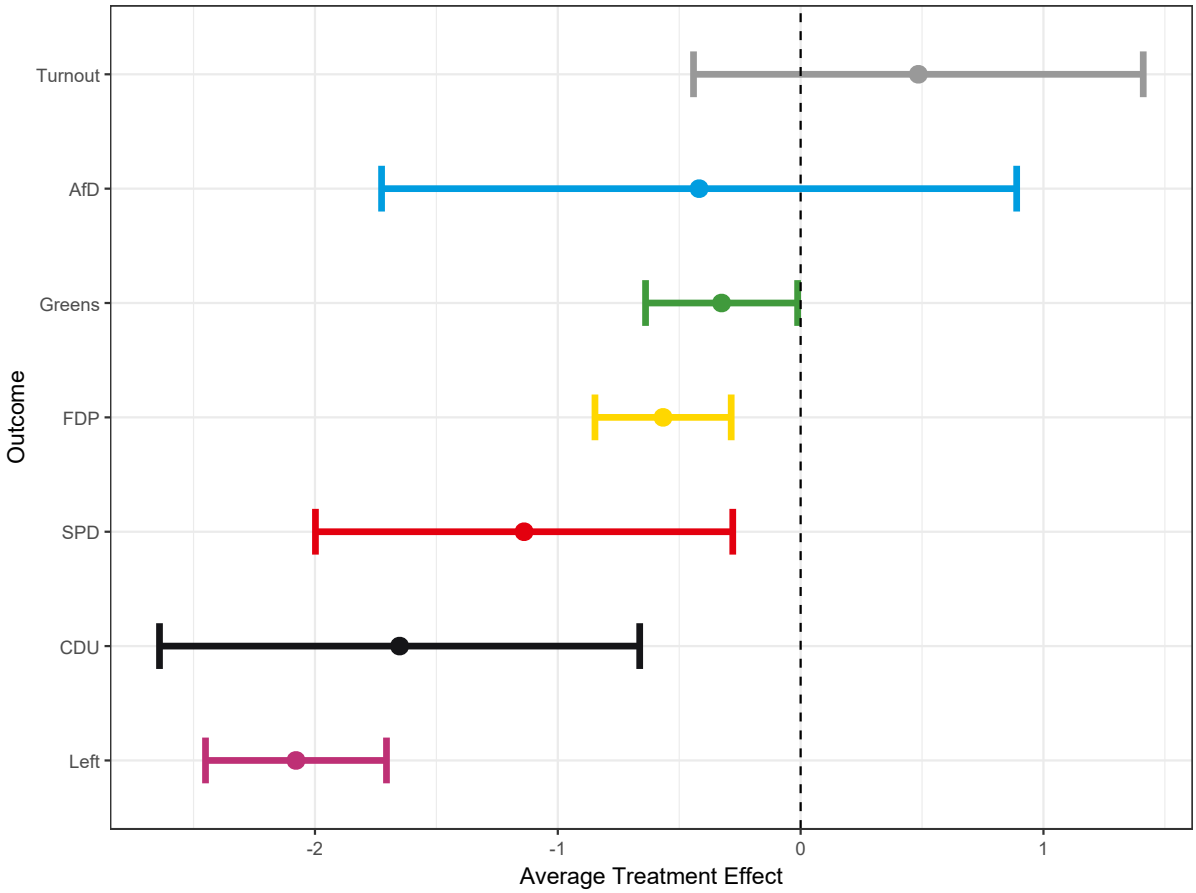
Note: We run an hierarchical model with random intercepts for counties instead of relying on clustered standard errors to explicitly model potentially correlated error terms of municipalities located within the same county.

Figure A5: Robustness Check: Adding Municipalities with Incomplete Party Competition



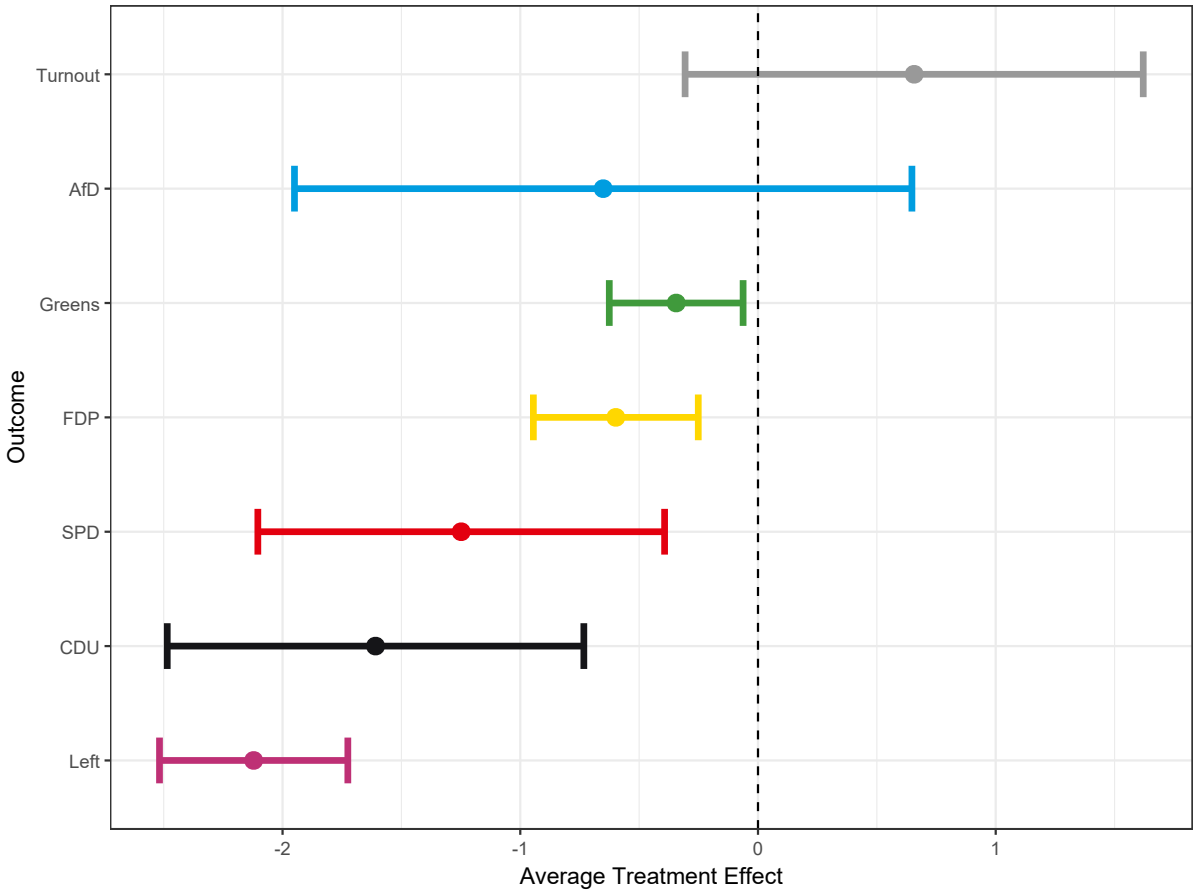
Note: We include 78 municipalities with ”incomplete” party competition, i.e., where not all nationally relevant parties contested the 2024 County Council election. Rather than excluding these cases as in the main sample, we follow Jankowski et al. (2022) and set the vote share of noncompeting parties to 0. This test assesses the sensitivity of the results to variations in party competition composition.

Figure A6: Robustness Check: Entropy Balancing as Alternative Weighting Method



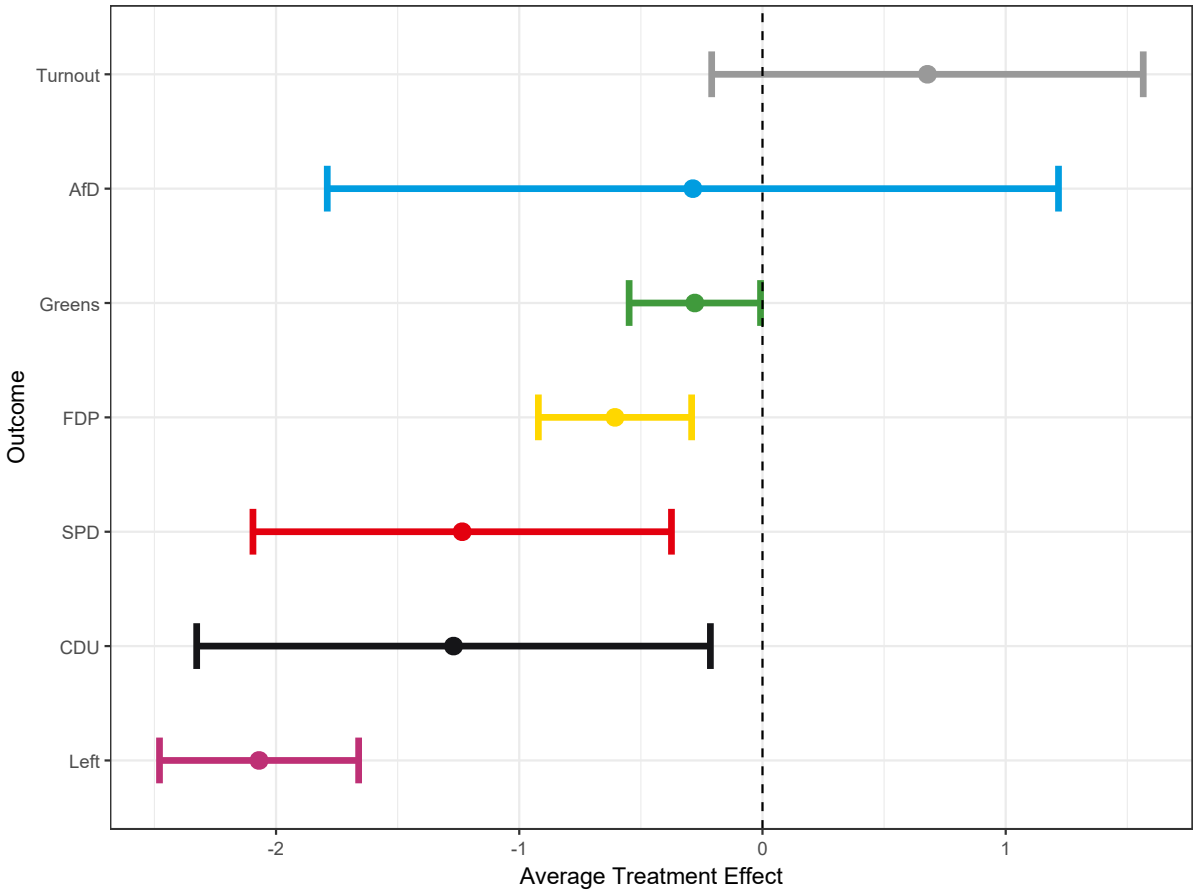
Note: We apply entropy balancing as an alternative method to generate weights (Hainmueller 2012). This ensures that our findings are not dependent on the specific choice of CBPS for generating weights.

Figure A7: Robustness Check: Dropping Municipalities with Imputed Values



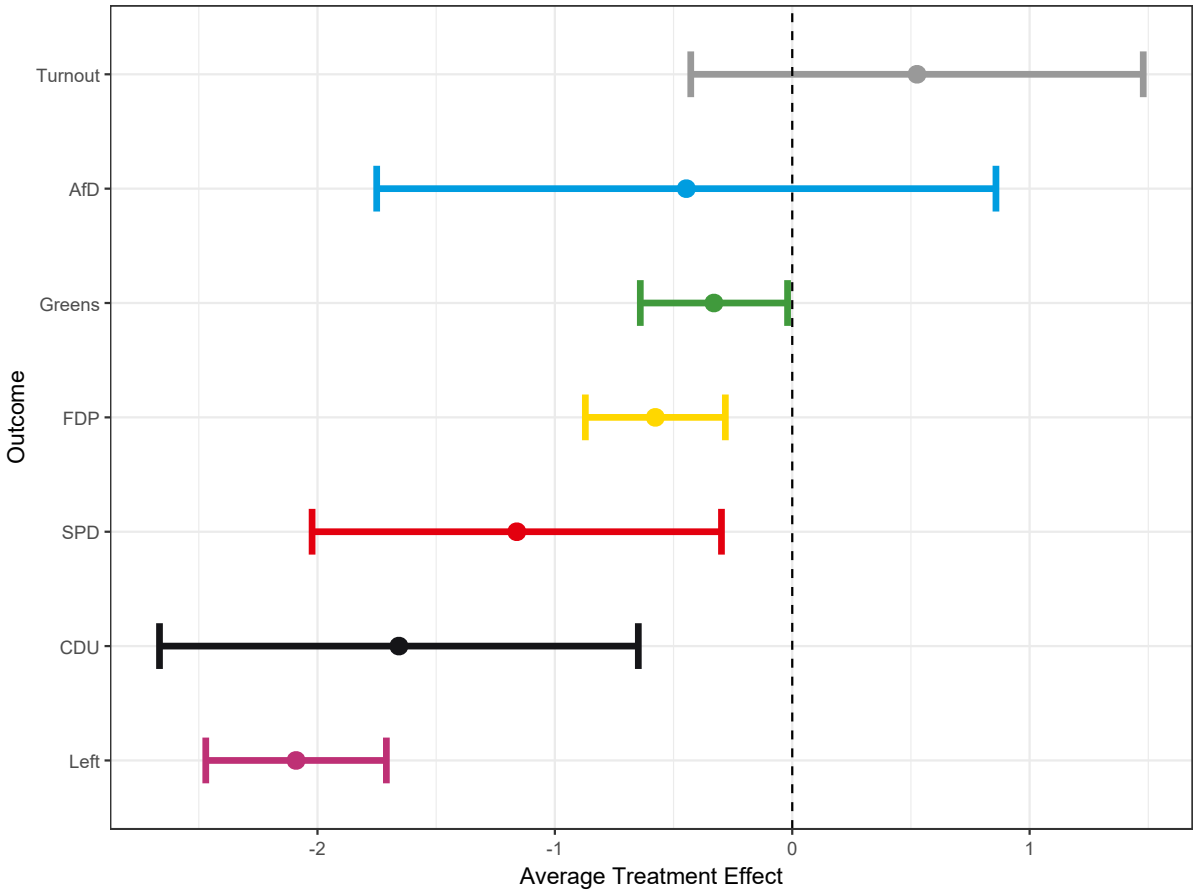
Note: We exclude 50 municipalities with imputed values for the share of foreigners, testing whether the imputation process from county-level data affects our results.

Figure A8: Robustness Check: Dropping Observations from Saarland



Note: We remove all observations from Saarland, where voters only get to choose among closed party lists in County Council elections, unlike the open-list ballots used in the remaining four states (Linhart and Eichhorn 2024). By excluding Saarland, we ensure that differences in voting systems do not confound the findings.

Figure A9: Robustness Check: Sensitivity Analysis of Weights



Note: We examine the sensitivity of our results to observations outside the common support of the propensity score, a standard robustness check when applying weighting methods (Caliendo and Kopeinig 2008). Specifically, we remove control units with propensity scores below 0.16 and treatment units with scores above 0.84. This minimizes the influence of observations with extremely low or high weights, which could otherwise disproportionately affect the estimates.

Data Availability & Replication Material

All data and R scripts necessary to replicate the results of this study are publicly available in a Dataverse repository (Eschenwecker and König 2024).

References

Bertelsmann Stiftung. 2024. Wegweiser Kommune. https://www.wegweiser-kommune.de/. Accessed 7 October 2024.

Bundesamt für Kartographie und Geodäsie. 2024. Verwaltungsgebiete 1:5 000 000, Stand 31.12.2023. https://gdz.bkg.bund.de/index.php/default/digitale-geodaten/verwaltungsgebiete/verwaltungsgebiete-1-5-000-000-stand-31-12-vg5000-12-31.html. Accessed 7 October 2024.

Caliendo, Marco and Sabine Kopeinig. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22(1): 31–72.

Eschenwecker, Stefan and Thomas König. 2024. Replication Data for: Challenging the Challengers? Quasi-Experimental Evidence on the Impact of the Bündnis Sahra Wagenknecht on German Party Competition. Version V2. https://doi.org/10.7910/DVN/PYOHGA.

Greifer, Noah. 2024a. cobalt: Covariate Balance Tables and Plots. https://CRAN.R-project.org/package=cobalt. R package version 4.5.5.

Greifer, Noah. 2024b. WeightIt: Weighting for Covariate Balance in Observational Studies. https://CRAN.R-project.org/package=WeightIt. R package version 1.3.2.

Hainmueller, Jens. 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis* 20(1): 25–46.

Imbens, Guido W. 2004. Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics* 86(1): 4–29.

Jankowski, Michael, Christina-Marie Juen, and Markus Tepe. 2022. The impact of anti-establishment parties on the electoral success of independent local lists: Evidence from Germany. *Party Politics* 28(1): 127–136.

Linhart, Eric and Kristin Eichhorn. 2024. Electoral systems and party systems in germany on the local level. *German Politics* 33(3): 584–610.

Rubin, Donald B. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology* 66(5): 688.